IEEE IMCEC(ISSN:2693-2776)

2022 IEEE 5th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC) | 978-1-6654-7968-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/IMCEC55388.2022.10019866

Mushroom Recognition and Classification Based on Convolutional Neural Network

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***Abstract*—Mushroom as a common plant, its high nutritional value, but pick wild mushrooms up the mountain, identify the variety of mushrooms is a problem, every year due to accidental eating of wild poisonous mushroom poisoning incidents occur.Therefore, how to accurately identify the species of mushrooms is a problem with great research significance and value. With the development of computer technology such as deep learning and neural networks, many researchers have applied neural networks to the field of image recognition, including the recognition of mushrooms. In view of these situations, this paper uses convolutional neural network to realize the identification of mushroom species. In this paper, the MobileNetV2 network model is introduced, and the deep learning neural network model is used to train the data set obtained from kaggle to achieve the recognition of mushroom species. And the recognition algorithm is improved by removing dirty data and removing image background. The experimental results proved that the accuracy reached about 99.88% on the training set and about 81.25% on the validation set.**

Keywords—convolutional neural network; mushroom recognition; MobileNetV2; Deep learning.

I. INTRODUCTION

Most of the current methods for mushroom recognition[1] are still the traditional methods of observing the image of mushroom features based on experience and assay detection, but with the rapid development of deep learning, convolutional neural networks have gradually started to be applied to mushroom recognition. Xiao JW[2] et al. used the lightweight ShuffleNetV2 model to solve the difficulties of mushroom image classification to some extent. Liu B[3] et al. proposed a mushroom recognition method based on Bayesian classification model to address the shortcomings of traditional mushroom recognition methods, which achieved an accuracy of over 98% for poisonous mushrooms. Luo Qi[4] proposed a reduced-gradient convolutional training model.The recognition rate and accuracy of this model are better than those of traditional convolutional neural networks, and good experimental results have been achieved in mushroom image classification. Pang F[5] et al. proposed a BP neural network-based mushroom identification method to identify unknown poisonous mushrooms by understanding the features of known poisonous mushrooms. Fadlil A[6] et al. proposed a mushroom image recognition method using Orde 1 statistical feature extraction and artificial neuron network with an accuracy of 93% for neuron 20. Dong J[7] et al. proposed an automatic classification algorithm for enoki mushroom caps. and established a LeNet-based convolutional neural network model to achieve the recognition of enoki mushroom caps. Zhao H et al.[8] trained VGG16, Resnet18 and Googlenet models and integrated them by bagging algorithm to improve the accuracy and generalization ability, and the accuracy of the integrated model by 10% Holdout validation dataset was 93.1% for the integrated model and 90.8% for the single bagging integrated model.

This paper firstly introduces the current progress in mushroom recognition, the second chapter gives a more detailed description and analysis of the MobileNetV2 model architecture, the third chapter introduces the convolutional neural network to solve the mushroom image recognition problem, completes the training of the mushroom image data set, and optimizes the algorithm by removing the dirty data and removing the image background. Finally, the main work of this paper is summarized, and the shortcomings of the experiments, the aspects to be improved and the prospects for future work are objectively pointed out.

II. RELATED WORK

A. MobileNetV2

MobileNet v2[9] network was proposed by google team in 2018, which has higher accuracy and smaller model compared to MobileNet V1 network. Highlights in the network : Inverted Residuals[10] ,Linear Bottlenecks .

1) Inverted Residuals

In the previous ResNet residual structure is the operation of dimensionality reduction by 1x1 convolution and then dimensionality increase. And in MobileNetV2, it is the operation of dimensioning up first and then dimensioning down. So for the ResNet residual structure, the two ends are large and the middle is small. For MobileNetV2 structure, it is large in the middle and small at both ends. In the MobileNet structure, a new activation function is used: ReLU6

$$y = \mathrm{ReLU6}(x) = \min(\max(x, 0), 6)$$

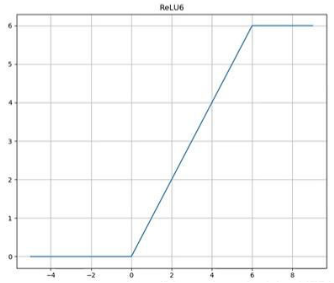

Fig. 1. ReLU6

2) *Linear Bottlenecks*

For the last convolutional layer in the inverse residual structure, a linear activation function is used instead of the ReLU activation function.

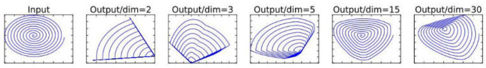

Figure 1: Examples of ReLU transformations of low-dimensional manifolds embedded in higher-dimensional spaces. In these examples the initial spiral is embedded into an n-dimensional space using random matrix T followed by ReLU, and then projected back to the 2D space using T^{-1}. In examples above $n = 2, 3$ result in information loss where certain points of the manifold collapse into each other, while for $n = 15$ to 30 the transformation is highly non-convex.

Fig. 2. Using linear activation function

One explanation is that the ReLU activation function may cause a relatively large instantaneous loss for low-dimensional information, while it causes little loss for high-dimensional feature information. Moreover, since the inverse residual structure is small at both ends and large in the middle, the output is a low-dimensional feature information. So a linear activation function is used to avoid feature loss. The structure is shown in Figure 3.

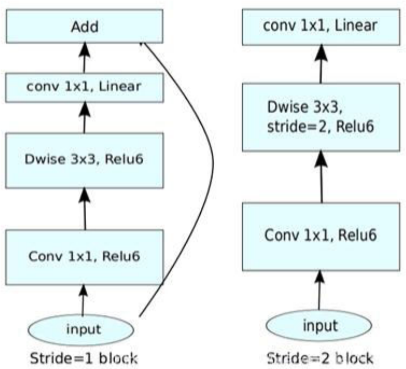

Fig. 3. Structure of feature information extraction

ps: when stride=1 and the input feature matrix is the same as the output feature matrix shape, there is a change in the shortcut connection shape: where k is the expansion factor.

Input	Operator	Output
$h \times w \times k$	1x1 conv2d , ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Fig. 4. Operation process

B. *Performance statistics of MobileNetV2*

Classification tasks

Network	Top 1	Params	MAdds	CPU
MobileNetV1	70.6	4.2M	575M	113ms
ShuffleNet (1.5)	71.5	**3.4M**	292M	-
ShuffleNet (x2)	73.7	5.4M	524M	-
NasNet-A	74.0	5.3M	564M	183ms
MobileNetV2	**72.0**	**3.4M**	**300M**	**75ms**
MobileNetV2 (1.4)	**74.7**	6.9M	585M	**143ms**

Fig. 5. Classification tasks

Where 1.4 in MobileNetV2 (1.4) stands for the multiplicity factor which is α, where α is the hyperparameter that controls the number of convolution kernels in the convolution layer and β is the size of the input image. It can be seen that it takes 75ms to classify an image main on the CPU, which basically meets the real-time requirement.

Object Detection Object detection tasks

Network	mAP	Params	MAdd	CPU
SSD300[34]	23.2	36.1M	35.2B	-
SSD512[34]	26.8	36.1M	99.5B	-
YOLOv2[35]	21.6	50.7M	17.5B	-
MNet V1 + SSDLite	22.2	5.1M	1.3B	270ms
MNet V2 + SSDLite	22.1	**4.3M**	**0.8B**	200ms

Fig. 6. Target detection task

As you can see, the proposed MobileNetV2 has basically made it possible to run deep learning models on mobile devices or embedded devices. It combines research with daily life.

III. Identification Results and Improvement

We use a data set from kaggle, this data set has 9 categories of the most common mushroom images, the data set has a total of 8516 images, we divide them according to our ratio of 3:1:1, using 60% as training set, 20% as validation set and 20% as test set.

Accuracy of training set: 98.53%, accuracy of test set: 72.32%.

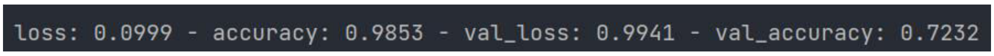

Fig. 7. Training results

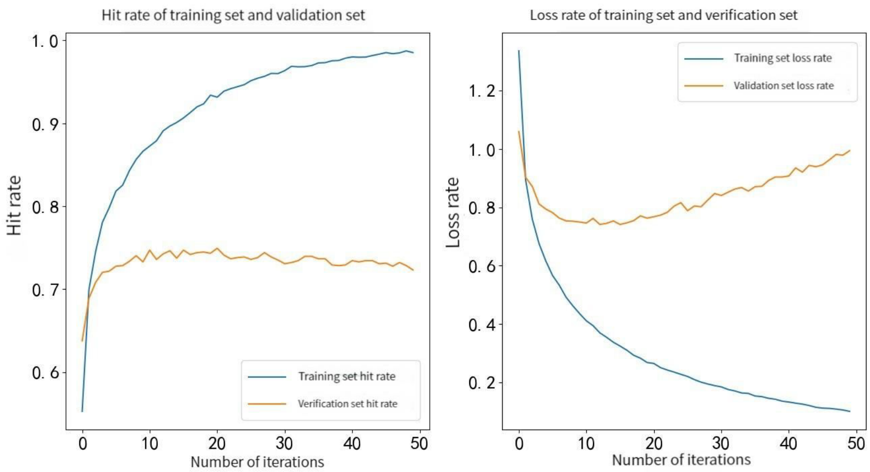

Fig. 8. Training result curve

The experimental results are not satisfactory. We tried to add dropout to the model and found that we did not get any improvement in detection performance. We analyzed and concluded that there is more dirty data in the dataset, which affects the recognition and classification of images by the network. Therefore, we use the method of Johnathan Nader[11] to process the images. We downloaded and installed the backgroundremover library through pytorch, then traversed the original image and executed os.system('backgroundremover -i "'+original_file+'" -o "'+new_file+'"') command on the current image to remove the background of the image, and stored the The result is stored under another file. This command mainly identifies the image subject and removes the image background to get a clean background and image subject, or if no subject is identified, this image will be deleted directly. After using the method of removing dirty data and de-backgrounding the image, we trained the model and got the result of the training set accuracy: 99.88% and the test set accuracy: 81.25%.

Fig. 9. Training results after removing dirty data

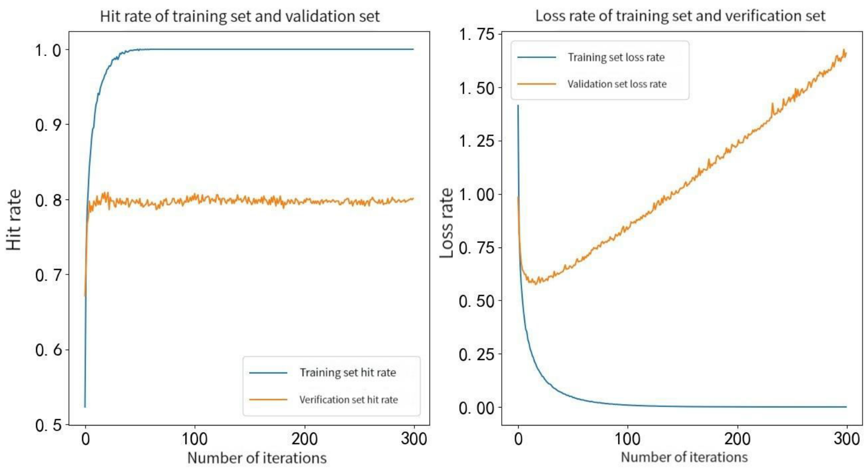

Fig. 10. Training result curve after removing dirty data

IV. CONCLUSION

With the development of deep learning and neural networks, the introduction of convolutional neural networks is proposed to solve the mushroom recognition problem for the shortcomings of traditional methods for mushroom recognition such as low accuracy and tedious operation. In this paper, the MobileNetV2 network architecture is introduced, and the model is optimized to improve the speed and accuracy of mushroom recognition by removing dirty data and removing background operations. However, there is still a poor recognition effect for partially obscured mushrooms, and we will conduct further research in this direction in the future.

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